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ANALYZING CORTICAL NETWORK DYNAMICS WITH RESPECT TO DIFFERENT CONNECTIVITY ASSUMPTIONS

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ABSTRACT
Current studies of cortical network dynamics are usually based on purely random wiring. Generally, these studies are focused on a local scale, where about 10 percent of all possible connections are realized. Neuronal connections in the cortex, however, show a more complex spatial pattern composed of local and long-range patchy connections. Here, we ask to what extent the assumption of such geometric traits influences the resulting dynamical behavior of network models. Analyzing the characteristic measures describing spiking neuronal networks (e.g., firing rate, coefficient of variation, correlation coefficient), we ascertain and compare the dynamical state spaces of different types of networks. To include long-range connections, we enlarge the spatial scale, resulting in a much sparser connectivity than what is usually assumed. Similar to previous studies, we can distinguish between different dynamical states (e.g., synchronous regular firing), depending on the external input rate and the numerical relation between excitatory and inhibitory synaptic weights. Yet, local couplings in such sparsely connected networks seem to induce specific correlations. Moreover, we find that another regularity measure than the coefficient of variation is required.

KEY WORDS
neuronal cortical network, patchy connections, dynamical state space

1 Introduction

The architecture of the complex network constituting the primary visual cortex is presumably an essential determinant of its function. Currently, most simulations of cortical network dynamics are either based on randomly connected networks [1,2] or, if considering a spatial dimension, they focus on local couplings. However, neuroanatomical publications [3] demonstrate that the projections of cortical neurons are much more complex than these rather simple assumptions: On the one hand, at least half of all synapses of a cortical neuron target neighboring cells, within a range of about $r_{loc} = 300\mu$m, see Fig. 1 and 2. On the other hand, a certain number of synapses target cells located at a distance much larger than the typical local range. In addition, there

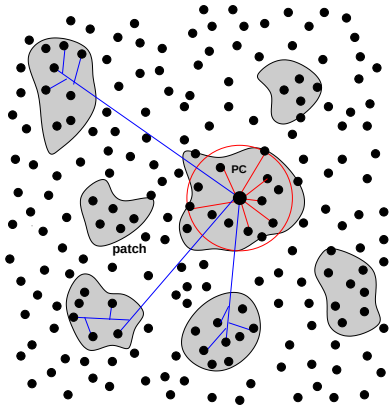

Figure 1. Top view representing a tracer injection in the gray matter of a flattened cortex. Black dots indicate neuron positions, and blue lines their patchy axonal ramifications. The gray area in the middle represents the stained halo surrounding the injection site, all other gray areas represent patchy projection sites.

is more and more evidence that 'patchy' projections (i.e., with spatially clustered projection targets, see Fig. 1 and 2) are not a rare exception but rather the general case. Here, we consider a large 2D piece of cortex representing layers 2/3 of cat VI, with spatially embedded neurons and assume distance dependent coupling rules. To include remote connections, we have to enlarge the usual spatial scale of about 1 mm side length. Thus, compared to [1,2], one neuron of our cortical network model is connected to a much smaller fraction of all other neurons: approximately one instead of ten percent.

The aim of this project is to investigate whether the results of previous studies on network dynamics hold for such spatially extended networks. As it is our focus to utilize realistic models and parameters, we consider two different types of conductance based integrate-and-fire (iaf) neurons, representing inhibitory (inh.) and excitatory (exc.) cells. The questions we try to answer are, for example: Do such realistic networks (i.e., small c, different parameters for exc. and inh. neurons) also exhibit different dynamical states (regular vs. irregular and synchronous vs.

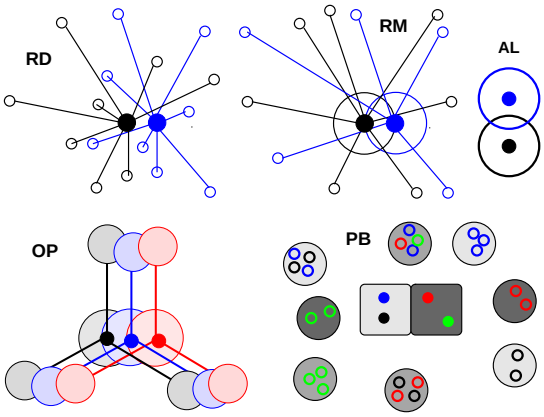

Figure 2. Models of different spatial arrangements of single cell projections: (RD) purely random connections, (RM) local and random remote couplings, (AL) purely local couplings, (OP) local couplings combined with overlapping patches for neighboring neurons, (PB) local couplings combined with shared patches: all neurons in a box project into three of six possible patches.

asynchronous firing [1]) depending on the external input rate and the numerical relation between excitatory and inhibitory synaptic weights? Do different connectivity patterns lead to different dynamical behavior, and are there certain aspects of these connectivities that induce specific firing patterns?

2 Methods

We consider $N = 49.163$ conductance-based iaf neurons randomly distributed in a 2D quadratic domain of extent $R = 5$ mm wrapped around to a torus. The global connectivity of all network models is $c = \bar{k}/N \approx 0.015$, with $\bar{k} =$ average number of outgoing synapses per neuron. According to [4] 78% of all neurons are excitatory (e) and 22% are inhibitory (i) (representing layers 2/3 of cat VI), with 71.1% ee, 9.96% ei, 16.14% ie and 2.8% ii connections. For the exc. and inh. populations we assume 60% and 73% local synapses, respectively. The neurons' local connectivity ranges are defined by half-Gaussians and are enlarged if all synapses are locally established. In case of patchy projections, each exc. or inh. neuron establishes on average three or two patches, with a radius and a mean distance from neuron to patch defined according to [3]. Fig. 2 shows the different network models that we plan to analyze in this project.

Differing from [1] we use conductance-based iaf neurons as in [2]. In contrast to [2] we utilize two different types of neurons: regular spiking exc. cells and fast spiking inh. cells, defined by the corresponding neuron parameters, see [5]. Each exc. neuron receives external poissonian input at a rate ν_{ext} while inh. neurons receive reduced rates $\nu_{ext} \cdot 0.66$. The exc. synaptic weights

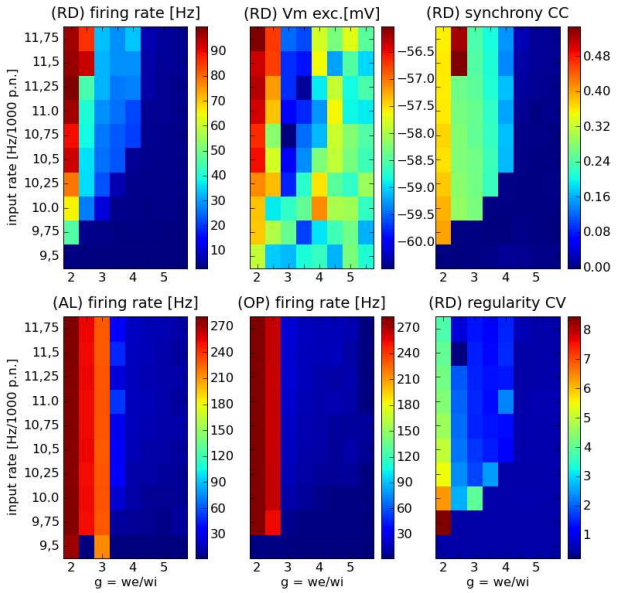

Figure 3. Dynamical state space analysis: Shown are the mean FR, the mean V_m (exc. population), the mean CC (upper row), and the CV (bottom right) of RD networks for varying g (x-axis) and ν_{ext} (y-axis). In addition, the mean FR of AL and OP networks (bottom row: left and middle) are presented.

w_e are set to produce EPSPs of 0.1mV peak amplitude while inh. synaptic weights are determined by the factor g: $w_i = g \cdot w_e$. To describe and analyze the network dynamics, we calculate the mean firing rate FR, the mean membrane potential V_m, the mean total conductance, the correlation coefficient CC, and the coefficient of variation $CV = \text{var}(ISI)/\text{mean}(ISI)^2$, where ISI stands for the Inter-Spike-Interval distribution. In case of a regular spiking neuron, we expect $CV = 0$, and $CV \approx 1$ for irregular poissonian spiking. Varying ν_{ext} and g, we explore the dynamical state space of our network models.

3 Preliminary Results

To adjust and to compare our results to previous studies, we started with the random network model. In general, our results for the RD network agree with [1,2]: As indicated by the simulation results in Fig. 3, large external input rates and low inhibition lead to a high FR, a high CC, a high V_m and high conductances (not shown). We also find different dynamical states depending on ν_{ext} and g: For small g (low inhibition), synchronous firing dominates, while increasing g and ν_{ext} leads to more asynchronous irregular firing, see Fig. 3 and 4.

The resulting values of the coefficient of variation, however, do not match the spike patterns in the corresponding raster plots: For example, $CV = 0.53$ in Fig. 4, top-left is not appropriate because of the irregular spike times

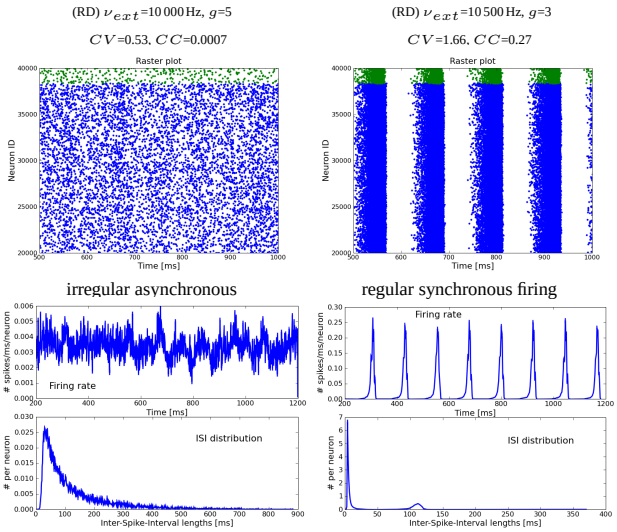

Figure 4. Exemplary raster plots of two network simulations with RD connectivity: Green dots represent inh. spikes, blue dots represent exc. spike timings. Bottom: The corresponding firing rates (1 ms bins) and ISI distributions.

($CV \approx 1$ is expected). Contrary, $CV = 1.66$ suggests irregular spiking for the rather regular spike times in Fig. 4, top-right. The bottom row of Fig. 4 shows the corresponding ISI distributions: on the left a typical exponential ISI distribution for an irregularly firing network (poissonian spike times). On the right, two main ISI lengths occur with high frequency, indicating a rather regular spiking. Thus, for a bimodal ISI distribution the normal CV is an inappropriate measure.

Concerning the network correlations, we find that local connections enhance the occurrence of synchronously occurring spikes, see Fig. 5. For identical ν_{ext} and g the RM, AL and OP networks exhibit stripy raster plots, while there are no such patterns in the RD network. Comparing the FR values of RD, AL and OP networks in Fig. 3, it is noticeable that the networks including local connections exhibit a sharp transition from low to very high firing rates while the RD networks smoothly change to a maximum of $FR = 100$ Hz.

4 Conclusion & outlook

Up to now, we show only preliminary results. The dynamical state space analysis (Fig. 3) has to be performed for a broader parameter range, and for all network types presented in Fig. 2. Likewise, it is necessary to employ another CV measure to correctly describe the (ir)regularity in our data. We are working on a so-called local version of the CV which is based on the Kullback-Leibler divergence of the ISI distribution. In addition, a distance dependend version of the correlation coefficient could provide more information about the network oscillations. Given all these improvements, we will be able to provide a detailed comparison of the dynamics of our five network models and to define a biologically realistic, stable background state. On top of this, a stimulus may be applied in order to analyze how the different connectivities influence the spatio-temporal spread of activity.

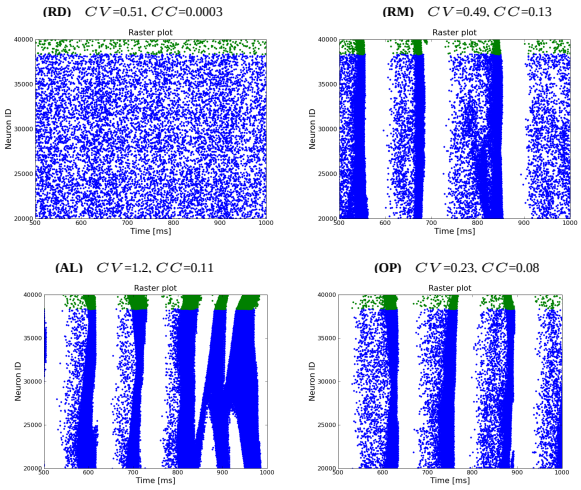

Figure 5. Exemplary raster plots of four network simulations with different connectivities, but for the same parameters $g = 3.5$ and ν_{ext}=10 000 Hz.

5 Acknowledgements

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